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Salgado et al.

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(54) **AGGLOMERATIVE ALGORITHM FOR GRAPH CLUSTERING**

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(51) **Int. Cl.**

G06F 8/41	(2018.01)
G06F 8/30	(2018.01)
G06F 9/38	(2018.01)
G06F 17/30	(2006.01)
G06F 16/35	(2019.01)

(52) **U.S. Cl.**

CPC ***G06F 8/443*** (2013.01); ***G06F 8/31*** (2013.01); ***G06F 9/3867*** (2013.01); ***G06F 16/358*** (2019.01)

(58) **Field of Classification Search**

CPC ... G06F 12/023; G06F 15/76; G06F 2212/251
USPC 711/154
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

8,243,988	B1 *	8/2012	Buddemeier	G06K 9/00677 382/103
8,966,457	B2 *	2/2015	Ebcioglu	G06F 17/5045 717/136
2010/0115206	A1 *	5/2010	de la Iglesia	G06F 12/0862 711/137
2010/0274785	A1 *	10/2010	Procopiuc	G06F 16/22 707/737
2017/0091342	A1 *	3/2017	Sun	G06F 16/9024
2017/0097884	A1 *	4/2017	Werner	G06F 12/023
2017/0142151	A1 *	5/2017	Jusko	H04L 63/1433
2017/0161038	A1 *	6/2017	Ottoni	G06F 16/9024

* cited by examiner

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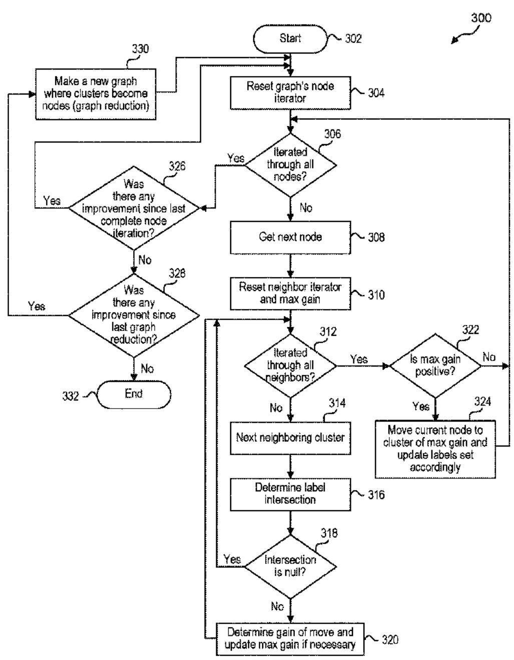
(57) **ABSTRACT**

Disclosed herein are system, method, and computer program product embodiments for determining clusters of operations in a data processing pipeline. By clustering the operations according to the operations' programming languages using the algorithm disclosed herein, performance efficiency gains can be achieved. The algorithm is iterative, traversing all operations in a data processing pipeline with subsequent iterations addressing the clustering regime determined by prior iterations.

20 Claims, 9 Drawing Sheets



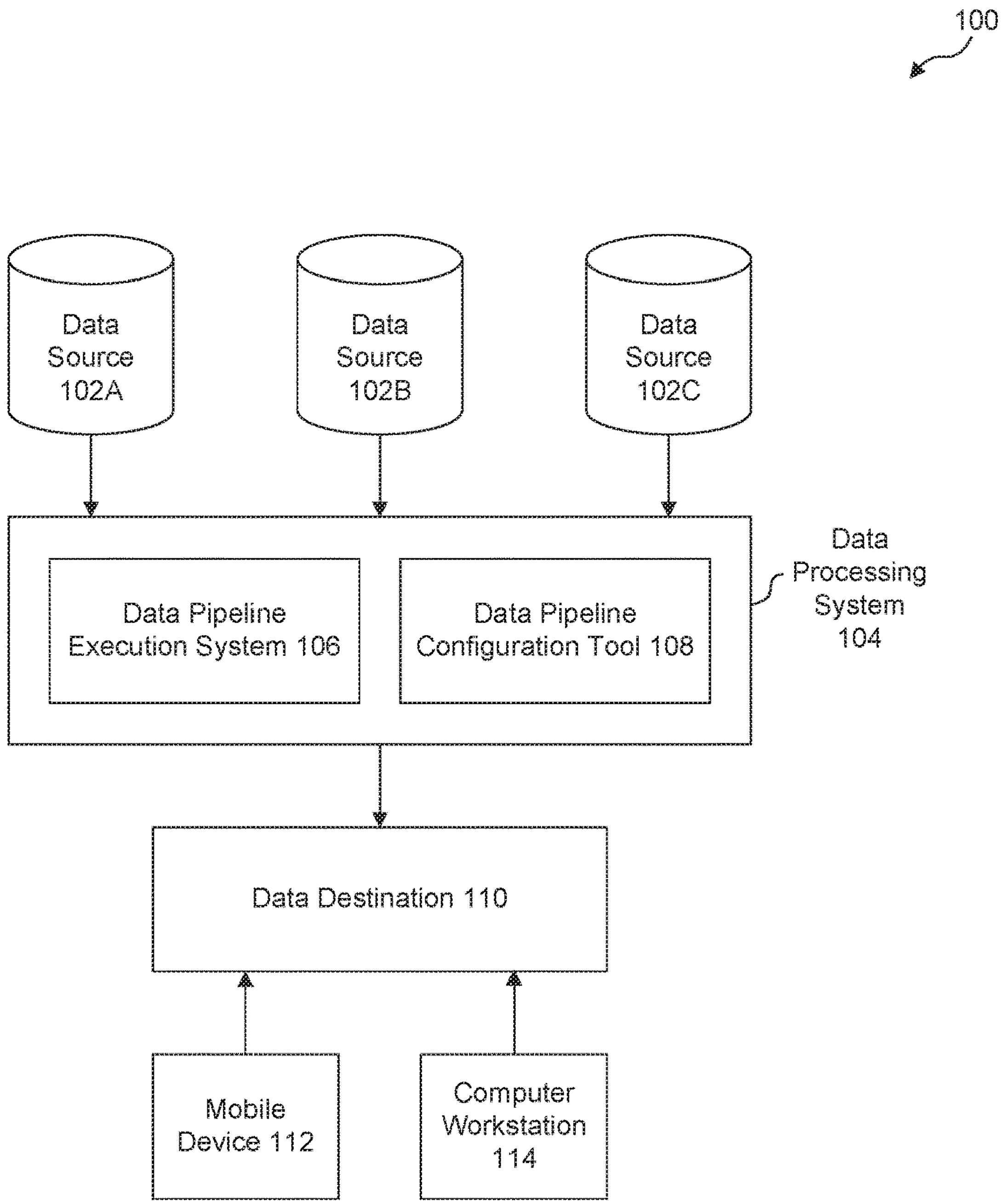


FIG. 1
PRIOR ART

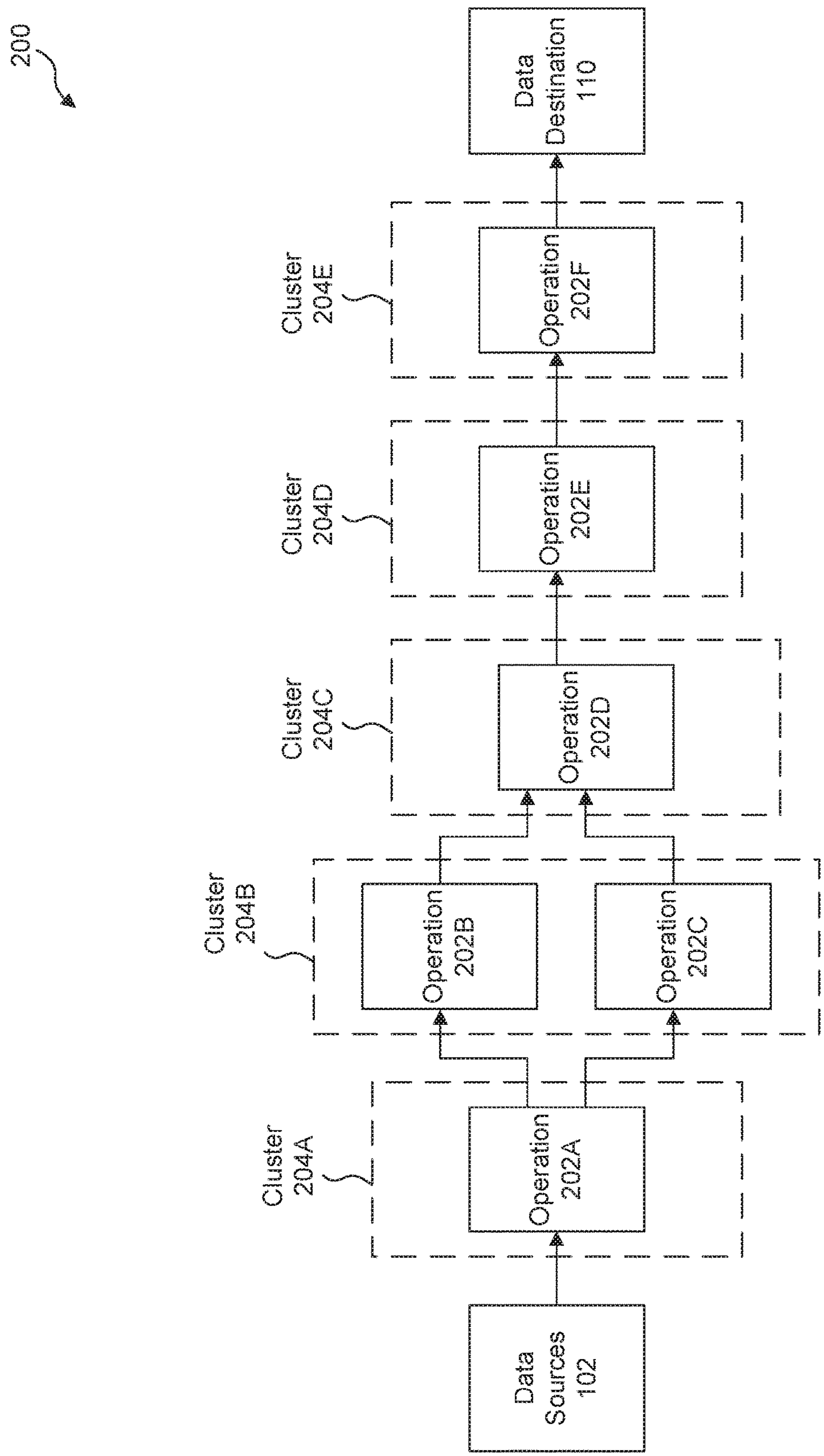

200
Data Sources 102
Cluster 204A
Operation 202A
Cluster 204B
Operation 202B
Operation 202C
Cluster 204C
Operation 202D
Cluster 204D
Operation 202E
Cluster 204E
Operation 202F
Data Destination 110

FIG. 2A

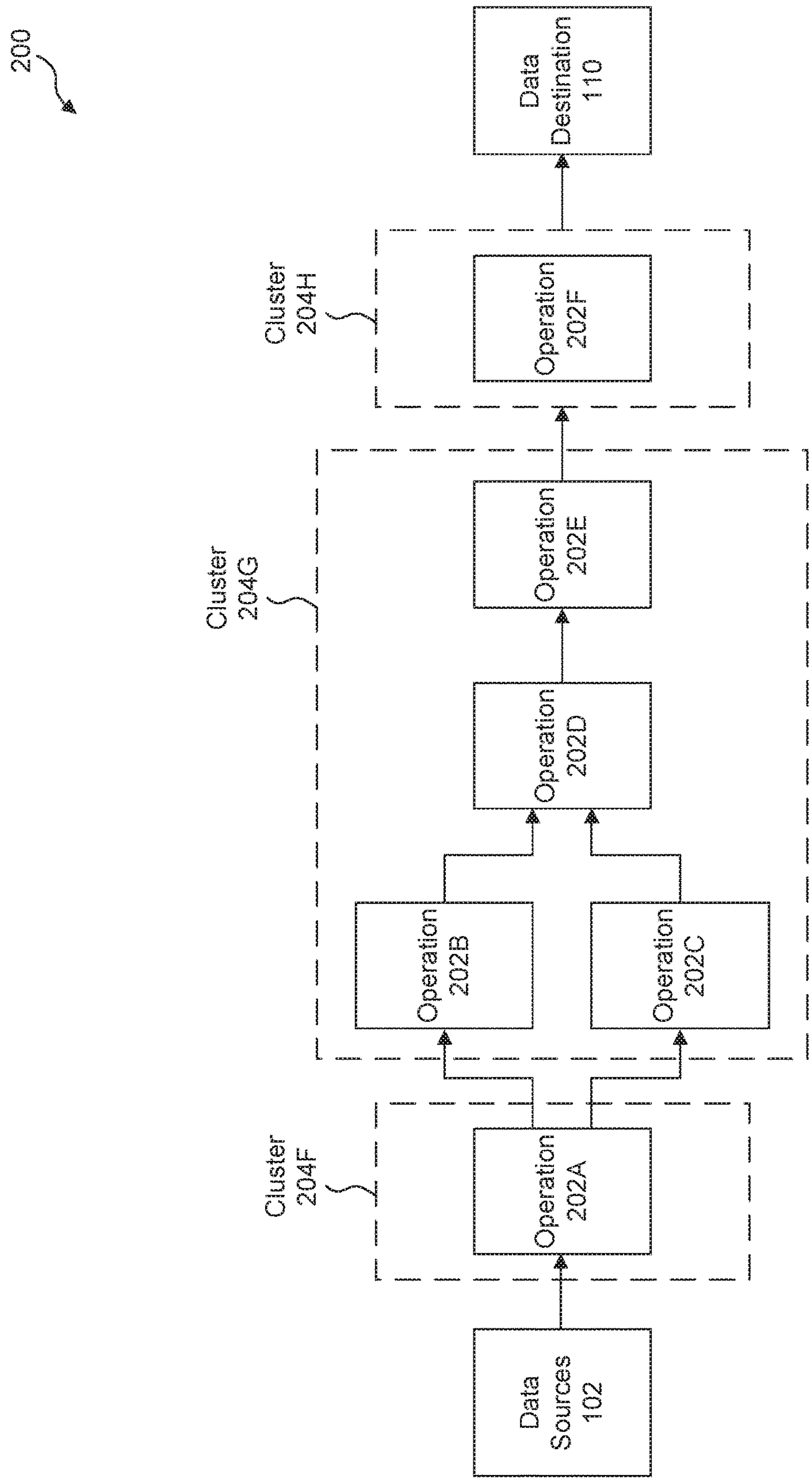

200
Data Sources 102
Cluster 204F
Operation 202A
Cluster 204G
Operation 202B
Operation 202C
Operation 202D
Operation 202E
Cluster 204H
Operation 202F
Data Destination 110

FIG. 2B

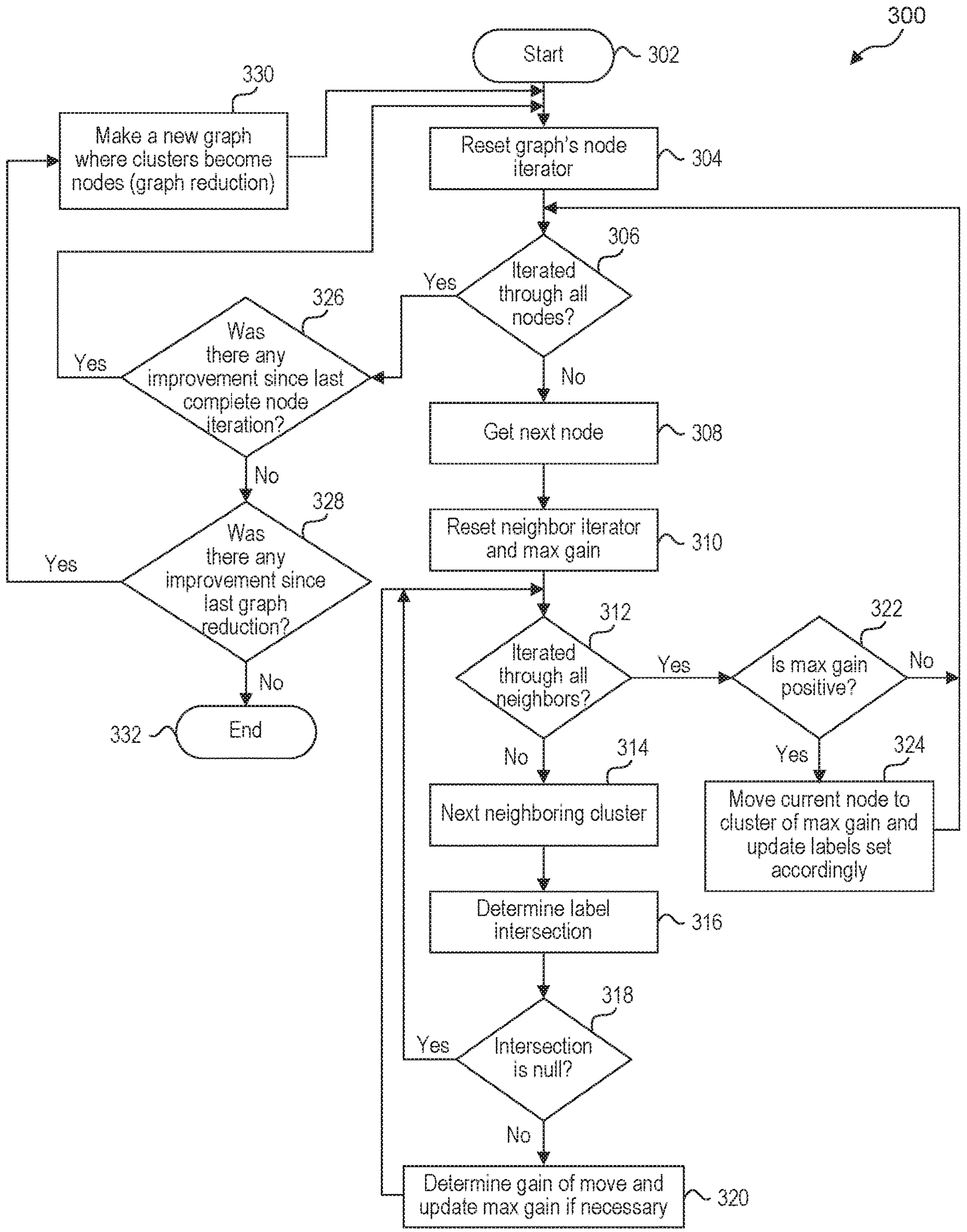

300
Start
302
Reset graph's node iterator
304
Iterated through all nodes?
306
Yes
No
Get next node
308
Reset neighbor iterator and max gain
310
Iterated through all neighbors?
312
Yes
No
Is max gain positive?
322
No
Yes
Move current node to cluster of max gain and update labels set accordingly
324
Next neighboring cluster
314
Determine label intersection
316
Intersection is null?
318
Yes
No
Determine gain of move and update max gain if necessary
320
Was there any improvement since last complete node iteration?
326
Yes
No
Was there any improvement since last graph reduction?
328
Yes
No
End
332
Make a new graph where clusters become nodes (graph reduction)
330

FIG. 3

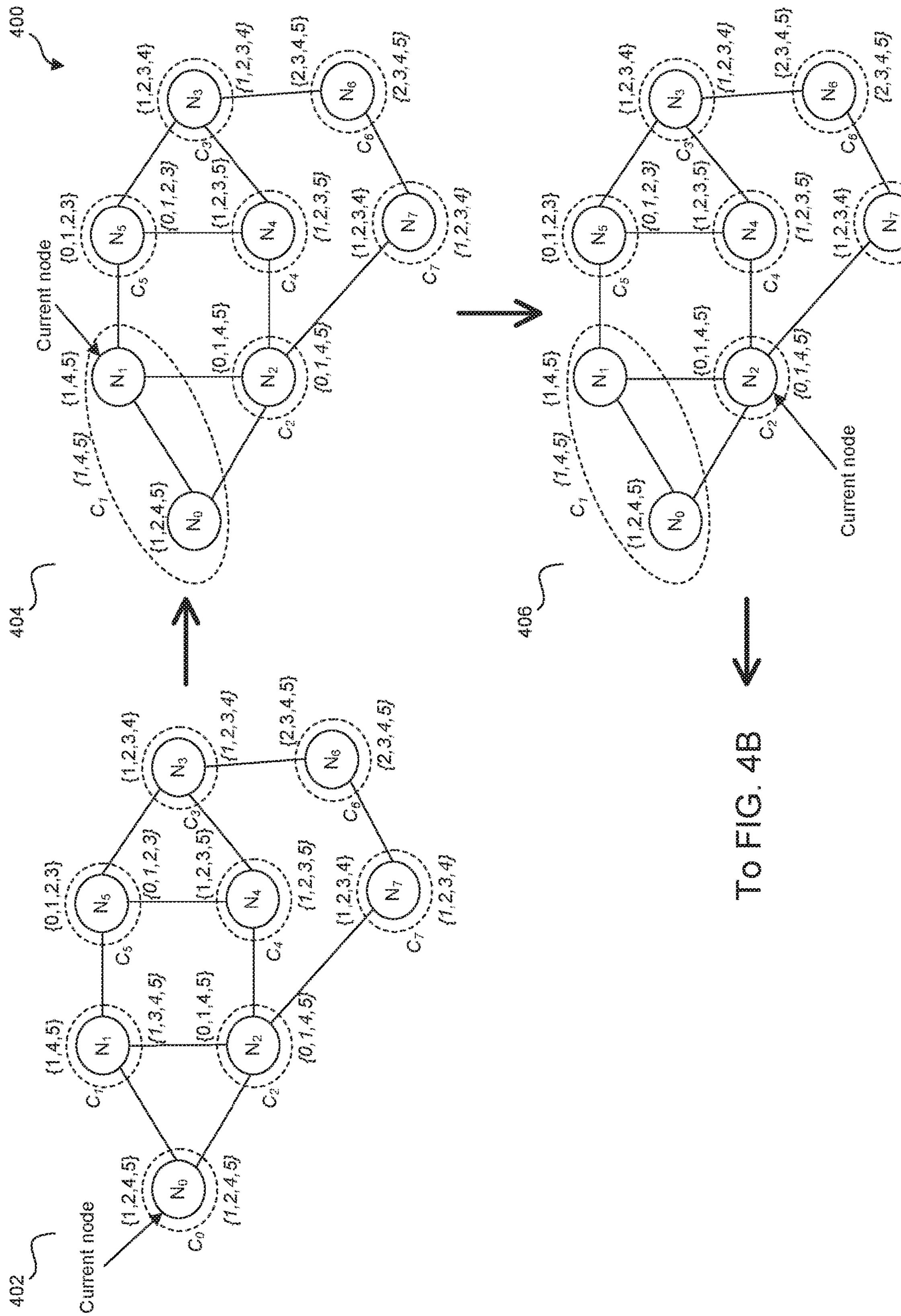

400
402
404
406
Current node
Current node
Current node
To FIG. 4B

FIG. 4A

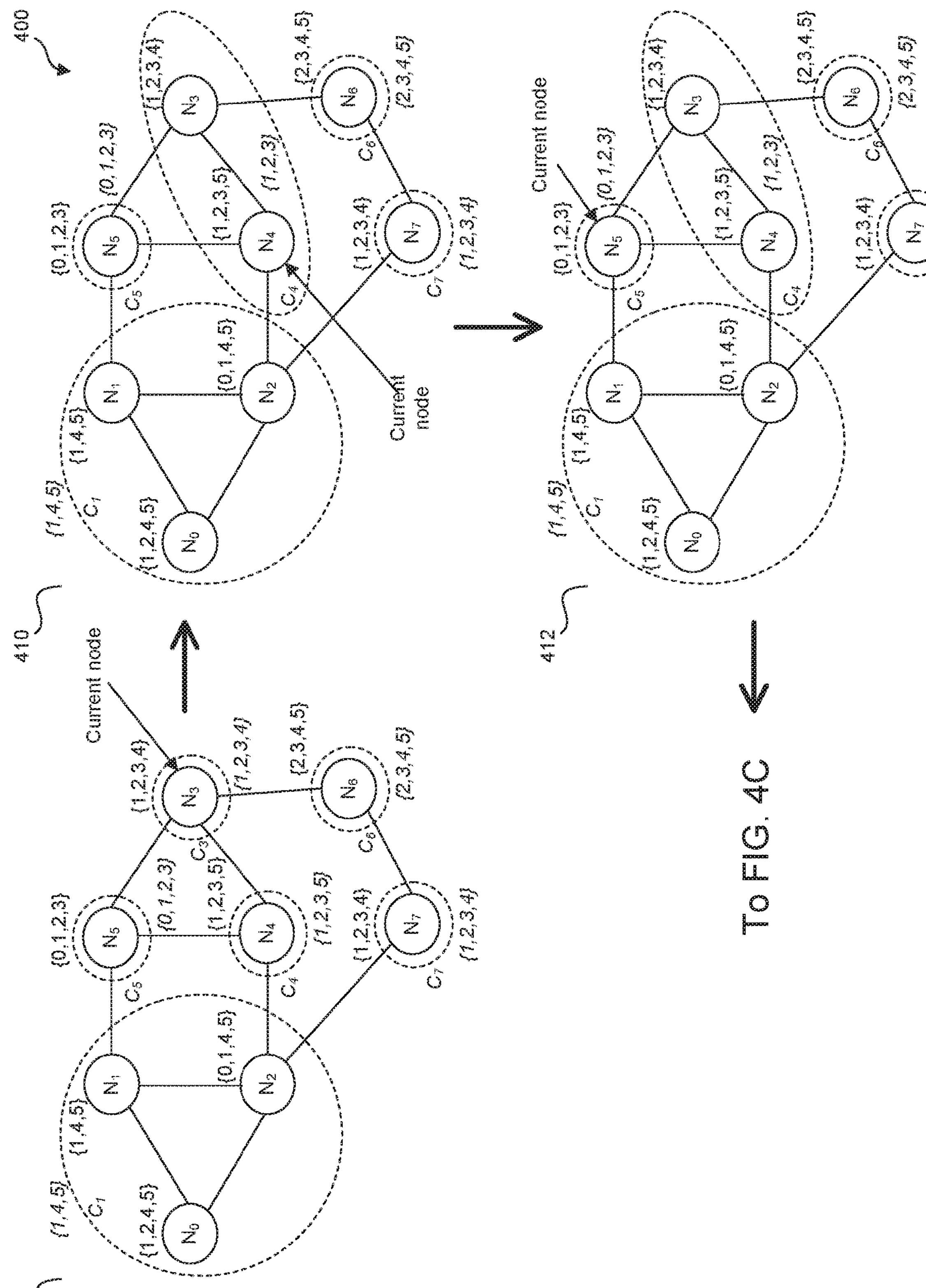

400
408
410
412
Current node
Current node
Current node
To FIG. 4C

FIG. 4B

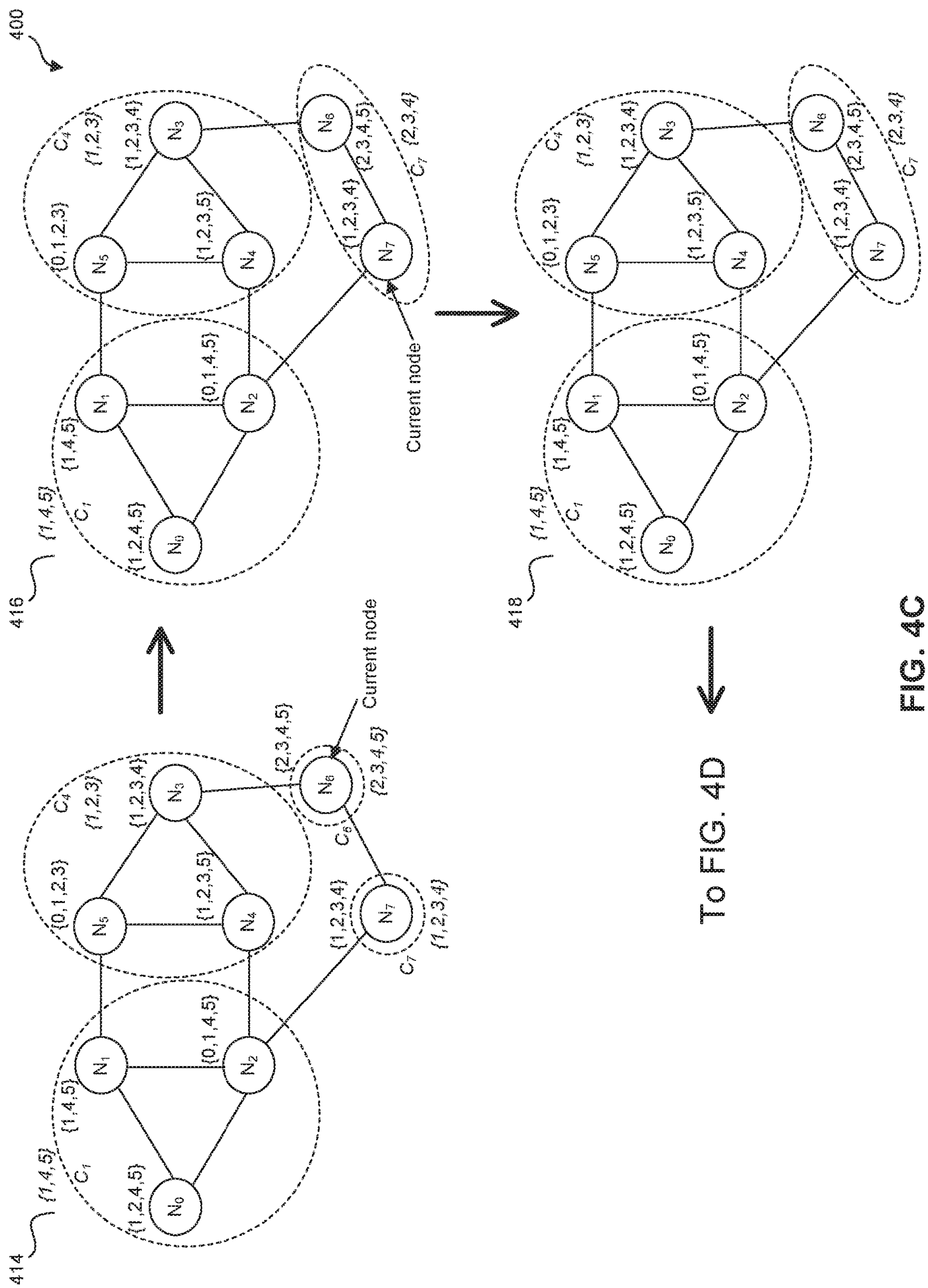

400
414
416
418
Current node
Current node
To FIG. 4D
N_0
N_1
N_2
N_3
N_4
N_5
N_6
N_7
C_1
C_4
C_6
C_7
{1,4,5}
{1,2,4,5}
{0,1,4,5}
{0,1,2,3}
{1,2,3,5}
{1,2,3,4}
{1,2,3}
{2,3,4,5}
{2,3,4}

FIG. 4C

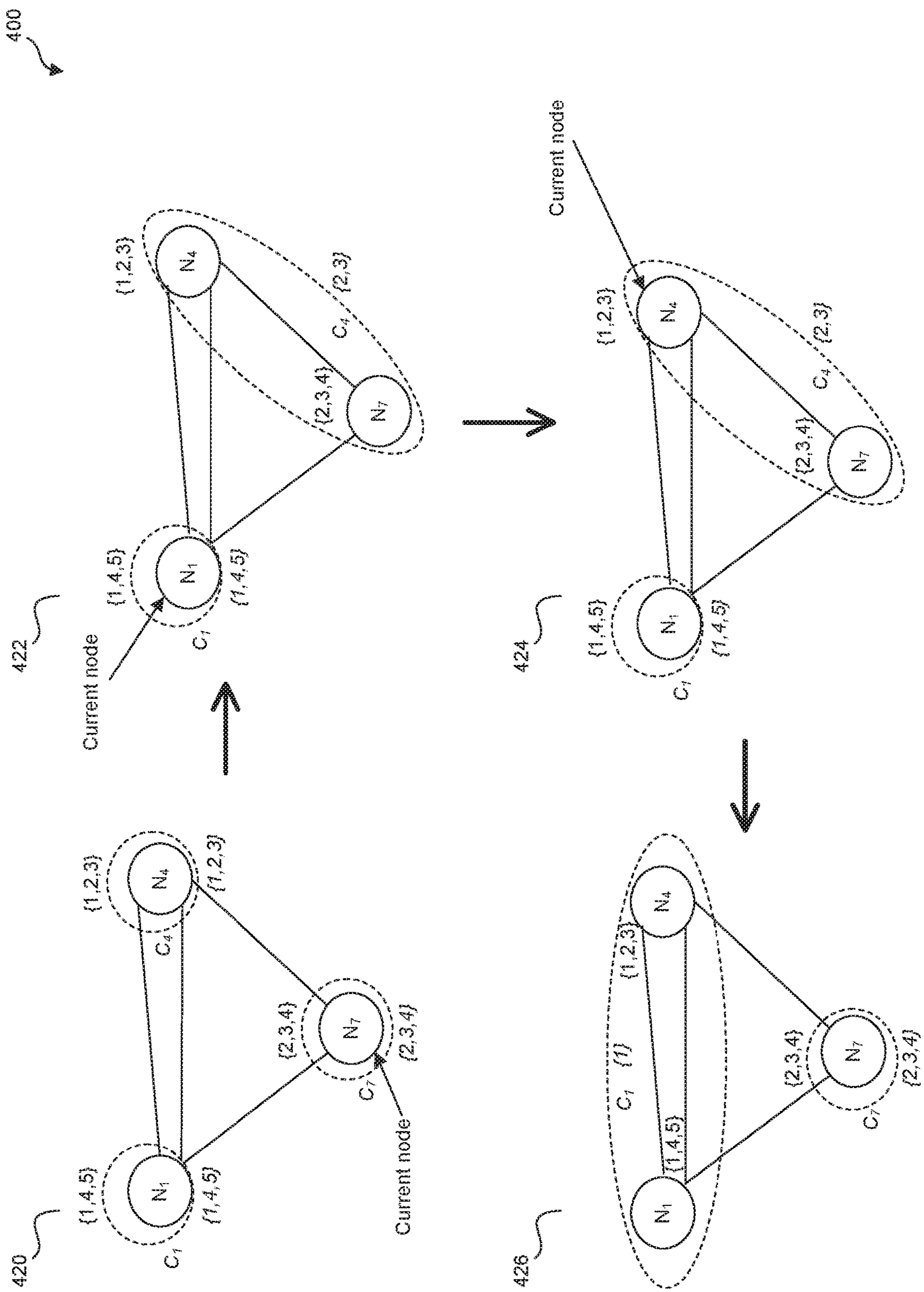

400
420
422
424
426
Current node
N_1
N_4
N_7
C_1
C_4
C_7
{1,4,5}
{1,2,3}
{2,3,4}
{2,3}
{1}

FIG. 4D

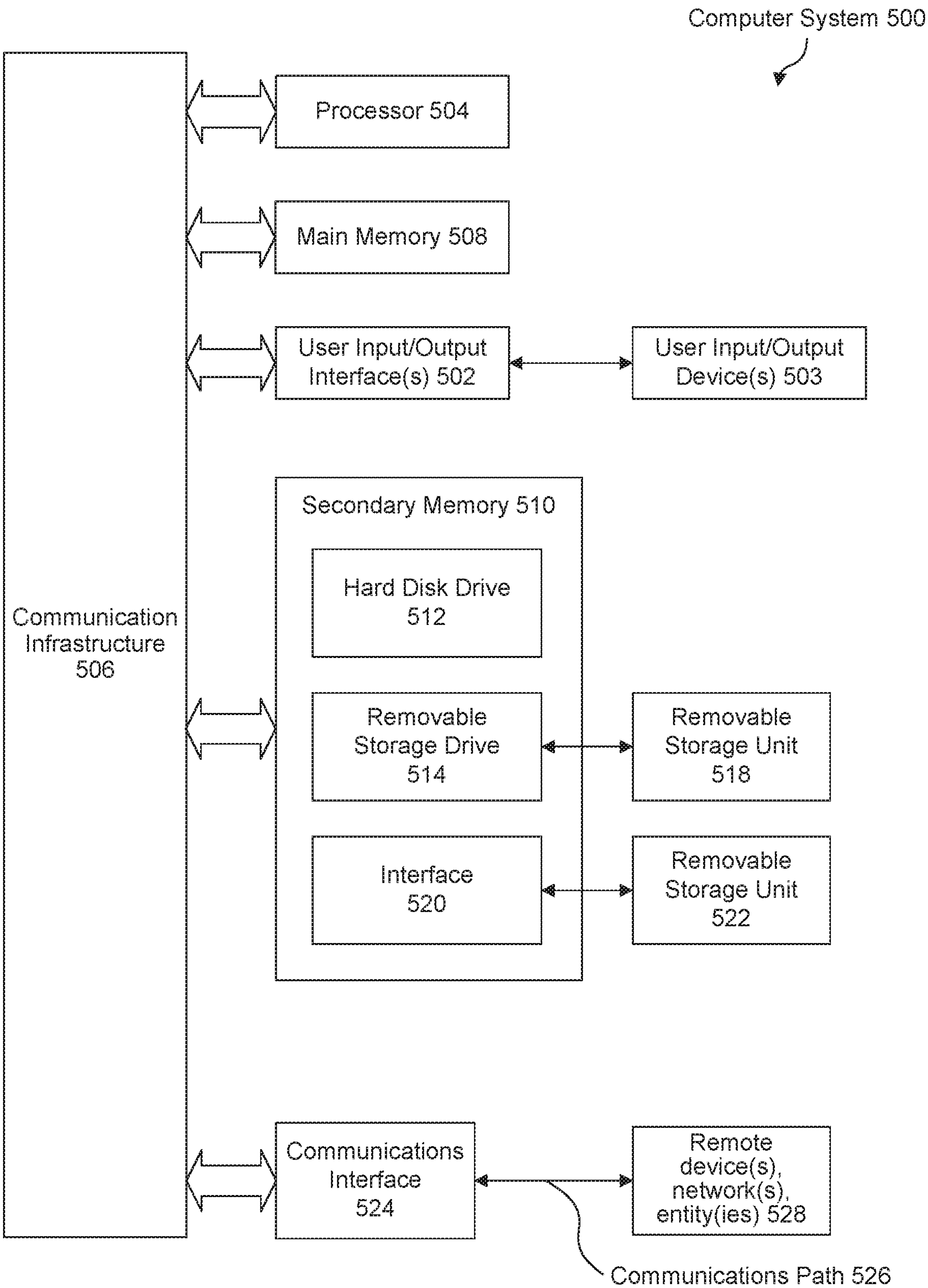

Computer System 500
Processor 504
Main Memory 508
User Input/Output Interface(s) 502
User Input/Output Device(s) 503
Secondary Memory 510
Hard Disk Drive 512
Communication Infrastructure 506
Removable Storage Drive 514
Removable Storage Unit 518
Interface 520
Removable Storage Unit 522
Communications Interface 524
Remote device(s), network(s), entity(ies) 528
Communications Path 526

FIG. 5

AGGLOMERATIVE ALGORITHM FOR GRAPH CLUSTERING

CROSS REFERENCE TO RELATED APPLICATIONS

This application claims the benefit of U.S. Provisional Patent Application 62/597,668, by Salgado, et al., "Agglomerative Algorithm for Graph Clustering," filed Dec. 12, 2017, which is hereby incorporated by reference in its entirety.

BACKGROUND

Generally speaking, organizations increasingly integrate vast amounts of data from a variety of sources and applications into big-data systems. Such big-data systems have been developed and deployed across most modern industries, including the financial and banking sectors, transportation services, entertainment industries, insurance, healthcare, education, medicine, retail, etc. The immense amount of data presents unique technical problems requiring distinct solutions because traditional data processing applications are unable to fully utilize and extract meaning from these gargantuan data sets, given their sheer scale.

Big-data applications have been developed that integrate, manage, and organize big-data systems, allowing organizations to harness the data's value for programmatic, analytical, diagnostic, or other suitable purposes. These big-data applications require specialized solutions for ingesting and transforming the data and facilitating communication between applications and platforms. These solutions must be highly optimized and efficient.

BRIEF DESCRIPTION OF THE DRAWINGS

The accompanying drawings, which are incorporated herein and form a part of the specification, illustrate embodiments of the present disclosure and, together with the description, further serve to explain the principles of the disclosure and to enable a person skilled in the arts to make and use the embodiments.

FIG. **1** is a block diagram of a data processing system, according to some embodiments.

FIGS. **2**A-**2**B are block diagrams of data processing pipelines utilizing clusters, according to some embodiments.

FIG. **3** is a flowchart illustrating a process for determining the clusters in a data processing pipeline, according to some embodiments.

FIGS. **4**A-**4**D are flowcharts illustrating an exemplary cluster determination for an exemplary data processing pipeline, according to some embodiments.

FIG. **5** is an example computer system useful for implementing various embodiments.

In the drawings, like reference numbers generally indicate identical or similar elements. Additionally, generally, the left-most digit(s) of a reference number identifies the drawing in which the reference number first appears.

DETAILED DESCRIPTION

Provided herein are system, apparatus, device, method and/or computer program product embodiments, and/or combinations and sub-combinations thereof, for determining clusters of operations in a data processing pipeline.

A data processing pipeline is a set of data-transforming or processing operations connected in a series or run in parallel.

An exemplary data processing pipeline could convert data from one format to another, present a visualization of the data, share data across applications, etc. In an embodiment, the data acted upon can be a data lake, message stream, relational database, semi-structured data (CSV, logs, xml, etc.), unstructured data, binary data (images, audio, video, etc.), or other suitable data repository. In an embodiment, the data sets processed are very large, having thousands, millions, billions, or trillions (or more) records.

Operations in a data processing pipeline can be predefined or custom-built functions or modules. Data processing pipelines including more than one operation may also specify connections between the operations. Thus, an operation may receive a data input, transform, modify, or otherwise operate upon the inputted data, and then pass the transformed data as output to a subsequent operation, component, or user to be further modified or acted upon. An operation may have zero or more inputs and zero or more outputs. The operations can also run in parallel, simultaneously, or other suitable fashion. In an embodiment, an operation may have been created in one or more programming languages. Additional performance costs arises when an operation programmed in one programming language passes large data sets to or receives large data sets from an operation programmed in a different programming language.

A cluster of operations is a logical construct by which the operations in a data processing pipeline can be grouped to enhance efficiency. In an embodiment, a performance gain occurs when grouping the operations by their programming languages because of the cost incurred if the operations have disparate programming languages.

In an embodiment, organizations can view the operations and their connections graphically in a visualization tool. Such a visualization tool allows organizations to easily specify operations and build data processing pipelines.

FIG. **1** is a block diagram illustrating environment **100** having a data processing system **104**, according to some embodiments. Any operation herein may be performed by any type of structure in the diagram, such as a module or dedicated device, in hardware, software, or any combination thereof. Any block in the block diagram of FIG. **1** may be regarded as a module, apparatus, dedicated device, general-purpose processor, engine, state machine, application, functional element, or related technology capable of and configured to perform its corresponding operation(s) described herein. Environment **100** includes data sources **102**, data processing system **104**, data pipeline execution system **106**, data pipeline configuration tool **108**, data destination **110**, mobile device(s) **112**, and computer workstation(s) **114**.

Data sources **102** are systems storing vast amounts of data in various forms. In an embodiment, data sources **102** could be database systems such as any suitable relational database product. Data sources **102** could further be message queues or stream processing platforms such as Apache Kafka or Apache Spark or other data storage systems like Apache Hadoop, HDFS, or Amazon S3, to name a few examples. In an embodiment, data sources **102** store thousands, millions, billions, or trillions (or more) of objects, rows, transactions, records, files, logs, etc. while allowing for the creation, retrieval, and management of this data. In an embodiment, data sources **102** utilize scalable, distributed computing to efficiently catalog the data.

Data processing system **104** includes data pipeline execution system **106** and data pipeline configuration tool **108**. Data processing system **104** transforms, converts, modifies, manages, transfers, adds to, subtracts from, analyzes or otherwise interacts with data from data sources **102** before passing the result to data destination **110**. Exemplary operations conducted within data processing system **104** could include: converting data from one format to another, preparing data for visualization, organizing the data, mining the data using regular expressions, natural language processors, or other mechanism, sharing data between different web applications, editing video/audio files, or any of a myriad of suitable interactions. In an embodiment, data processing system **104** executes these operations in real-time using parallel and distributed processing.

Data pipeline execution system **106**, a sub-component of data processing system **104**, receives data from data sources **102** and performs operations on the data before passing the data to data destination **110**. Data pipeline execution system **106** clusters the operations contained in the data processing system **104** to achieve performance gains, as is further detailed below. Data pipeline execution system **106** determines which operations to execute through a configuration specified through data pipeline configuration tool **108**.

Data pipeline configuration tool **108** allows an organization to create, modify, and edit data processing pipelines. In an embodiment, data pipeline configuration tool **108** provides a visualization tool whereby a data administrator can visualize the data processing pipeline in graphical form. Data pipeline configuration tool **108** can display any operations used in data pipeline execution system **106**, any connections between the operations, and the programming languages of each operation. In an embodiment, data pipeline configuration tool **108** provides the ability to add to, delete from, modify, or otherwise configure data processing system **104**.

Data destination **110** provides temporary or permanent storage for the transformed data and allows end users or ancillary computing components to view or interact with the transformed data. In an embodiment, data destination **110** can be a terminal, web browser, text file, excel spread sheet, graph, image file, or any other tool by which the data, as transformed by the data processing pipeline, can be visualized or otherwise interacted with. In an embodiment, data destination **110** provides advanced analytical mechanisms such as graphs, charts, or other visualization tools, providing further means by which to analyze the large data sets.

Mobile device(s) **112** and/or computer workstation(s) **114** provide end users a mechanism to view the transformed data, analytical representations of the transformed data, or other suitable portrayals thereof. In an embodiment, mobile device(s) **112** and computer workstation(s) **114** connect to data destination **110** via the Internet or other public network. In an alternate embodiment, data destination **110** and either mobile device(s) **112** or computer workstation(s) **114** reside on the same device.

FIG. **2**A is a block diagram illustrating an example data processing pipeline **200**. Any functionality herein may be performed by any type of structure in the diagram, such as a module or dedicated device, in hardware, software, or any combination thereof. Any block in the block diagram of FIG. **2**A may be regarded as a module, apparatus, dedicated device, general-purpose processor, engine, state machine, application, functional element, or related technology capable of and configured to perform its corresponding operation(s) described herein. Data processing pipeline **200** includes operations **202** and clusters **204**, as well as data sources **102** and data destination **110** detailed in FIG. **1**.

In FIG. **2**A, which is only one exemplary data processing pipeline **200**, data processing pipeline **200** includes cluster **204**A (encompassing operation **202**A), cluster **204**B (encompassing operation **202**B and operation **202**C), cluster **204**C (including operation **202**D), and cluster **204**E (encompassing operation **202**F). Here, clusters **204** are only an illustrative example of one particular embodiment. A potential inefficiency of the particular clustering arrangement in FIG. **2**A will become apparent during the below discussion of FIG. **2**B.

Operations **202** are functions, programs, modules, executables, or other behaviors that can be performed within data processing pipeline **200**. Operations **202** can perform a litany of exemplary functions such as: converting data format, deleting records from the data, validating the data, performing calculations using the data, filtering the data, aggregating the data, and many other suitable functions.

Operations **202**, when aggregated and run sequentially or in parallel, can perform more elaborate functions and tasks. For exemplary purposes, data processing pipeline **200** could receive as input a number of video files and perform a sequence of operations to identify particular objects in the various video files. Further operations in this exemplary data processing pipeline **200** could subsequently organize the matches into a spreadsheet and display the spreadsheet for review by a human being or ancillary computer component. One skilled in the relevant arts will appreciate the vast array of disparate tasks that could be accomplished by data processing system **104**, as well as the potentially complicated interactions between various operations **202** in data processing pipeline **200**.

In an embodiment, operations **202** receive a data input and transform, modify, observe, write to, or otherwise interact with the data input. Operations **202** can subsequently send or output the transformed data to another operation in operations **202** or to data destination **110**. In some embodiments, this passing of data between operations **202**, such as the data passing from operation **202**A to operation **202**B, will henceforth be referred to as occurring through connections, edges, inputs, or outputs. Operation **202**A may have zero or more inputs and zero or more outputs.

Operation **202**A may be implemented in different programming languages. In an embodiment, a programming language can be any set or group of related systems of symbols used for writing instructions in human-readable form. When connections between operations **202** connect an exemplary operation **202**A created in one particular programming language with exemplary operation **202**B created in a different programming language, performance inefficiencies can arise.

First, the data flowing through data processing system **104** may need to be copied entirely when the programming languages of operation **202**A and **202**B differ. When processing and manipulating large data sets, such a copy is an expensive transaction from a performance standpoint. Alternatively, in order to share a data set between operation **202**A and **202**B, the data can be serialized by operation **204**A and then deserialized by operation **202**B. Serialization involves converting the data set into a series of bytes for generalized storage. In an embodiment, Operation **202**B can then deserialize the data, i.e., convert it from the series of bytes back into a useable data object. Serializing and deserializing large data sets in this fashion can be time-consuming. On the other hand, if operation **202**A and operation **202**B share a programming language, then a reference or pointer to the data can be shared between operation **202**A and operation **202**B, negating the need for a deep copy or serialization/deserialization.

Second, when operation **202**A and operation **202**B have disparate programming languages, a separate and distinct operating system process may need to be spawned for operation **202**A and operation **202**B. As a data pipeline grows larger and more complex and complicated, memory utilization issues and blocking can arise due to multitudinous processes running in parallel. However, if operation **202**A and operation **202**B share a programming language, operation **202**A and operation **202**B can execute within a shared operating system process.

Operation **202**A could be programmed in any suitable programming language. Moreover, operation **202**A may have been programmed in more than one programming language. For instance, an exemplary operation **202**A can have been programmed in Python, C++, and Go. Accordingly, data pipeline execution system **106** can select between these versions of operation **202**A when executing operation **202**A.

Clusters **204** organize operations **202** to achieve efficiency gains when executing data processing pipeline **200**. In an embodiment, clusters **204** group operations **202** programmatically according to the programming languages of operations **202** in order to achieve an improved or optimized clustering regime. Clusters **204** can be thought of as logical constructs that are themselves associated with a set of programming languages. In other words, cluster **204**A would have a set of associated programming languages, cluster **204**B would have a set of associated programming languages, etc. A connection is an internal connection if the connection does not cross the boundary between different clusters **204** and is, instead, contained entirely within one cluster in clusters **204**.

In an embodiment, data pipeline execution system **106** determines the set of programming languages associated with clusters **204** using the programming languages of operations **202** encompassed by clusters **204**. In such an embodiment, the set of programming languages associated with cluster **204**A is the intersection of the programming languages of the operations **202** encompassed by cluster **204**A. One skilled in the arts will appreciate that an optimized clustering regime can achieve significant efficiency gains in light of the efficiency losses that occur when an operation **204**A connects to an operation **204**B programmed in a different programming language. Data destination **110**, described above in relation to FIG. **1**, receives the transformed data after operations **202** execute and complete.

FIG. **2**B is a block diagram illustrating example data processing pipeline **200**, which is clustered differently compared to data processing pipeline **200** displayed in FIG. **2**A. Any operations or operational flow depicted herein may be executed sequentially, or they may alternatively be executed concurrently, with more than one operation being performed simultaneously, or any combination of the above.

Any operation herein may be performed by any type of structure in the diagram, such as a module or dedicated device, in hardware, software, or any combination thereof. Any block in the block diagram of FIG. **2**B may be regarded as a module, apparatus, dedicated device, general-purpose processor, engine, state machine, application, functional element, or related technology capable of and configured to perform its corresponding operation(s) described herein.

FIG. **2**B shows data processing pipeline **200**, which includes cluster **204**F (encompassing operation **202**A), cluster **204**G (encompassing operation **202**B, operation **202**C, operation **202**D, and operation **202**E), and cluster **204**H (encompassing operation **202**F). In light of the foregoing discussion of FIG. **2**A, one skilled in the arts will understand that the clustering arrangement of FIG. **2**B could demonstrate improved efficiency as compared to the clustering arrangement of FIG. **2**A.

In FIG. **2**B, cluster **204**G requires that operation **204**B, operation **204**C, operation **204**D, and operation **204**E share a common programming language. Operations **202**B-**202**E could run or execute in the same programming language, as determined by the set of programming languages attributed to cluster **204**G. In other words, data pipeline execution system **106** could intelligently choose versions of operation **202**B, operation **202**C, operation **202**D, and operation **202**E having the same programming language. Such a cluster configuration would avoid any performance degradations from switching between operations **202** written in different languages. A deep copy of the data set could be avoided and the operations sharing a language consolidated into one operating system process.

One skilled in the arts will appreciate that even in the simple figure presented in FIGS. **2**A-**2**B, a massive amount of different clustering configurations can potentially be determined, depending upon the programming languages available for each operations **202**. Moreover, certain clustering configurations will be more efficient and beneficial than others. It is with this in mind that we will now discuss a method for determining clusters **204**.

FIG. **3** is a flowchart for method **300**, which determines clusters **204** for operations **202** in data processing pipeline **200**, according to an embodiment. Method **300** can be performed by processing logic that can comprise hardware (e.g., circuitry, dedicated logic, programmable logic, microcode, etc.), software (e.g., instructions executing on a processing device), or a combination thereof. It is to be appreciated that not all steps may be needed to perform the disclosure provided herein.

Throughout the discussion below, the term "nodes" will be used synonymously with operations **202**, as described in FIGS. **2**A-**2**B. Similarly, the programming languages associated with each operation in operations **202** will be referred to as a "set of labels" or "labels." A cluster will also have an associated "set of labels" or "labels."

In an embodiment, method **300** is implemented according to the following example pseudocode:

```
Input: A graph with a set of allowable labels for each node.
Output: A partition of the graph, and for each of its clusters, a set of labels that represents the
intersection of the label's set of its internal nodes.
outerImprovement = True
While outerImprovement:
    outerImprovement = False
    innerImprovement = True
    Initialize one cluster per node from graph
    While innerImprovement:
        innerImprovement = False
        For-each node in graph:
            maxGain = 0
            bestCluster = NULL
```

-continued

```
            For-each neighboring cluster of node:
                intersection = node.Labels ∩ neighborCluster.Labels
                If (intersection ≠ Ø and
                    gainOfMoving(node, neighborCluster) > maxGain):
                        bestCluster = neighborCluster
                    maxGain = gainOfMoving(node, neighborCluster)
            If maxGain > 0:
            innerImprovement = True
            outerImprovement = True
            moveToCluster(node, bestCluster)
If outerImprovement:
    Create new graph where its nodes are the clusters found and the edges are the ones
    which crosses them.
```

However, in other embodiments, method **300** can be implemented using other code/pseudocode/algorithms.

In **302**, method **300** commences. Initially, method **300** initializes one cluster for each node in the graph. In other words, the same number of clusters as nodes will exist, each cluster containing exactly one node. The set of labels associated with each cluster will be set to the set of labels (in an embodiment, the programming languages available for the operation) associated with the node encompassed.

In **304**, method **300** resets the graph's nodes iterator. A node iterator is a tool by which to traverse all nodes in data processing pipeline **200**. Such traversing may occur sequentially, randomly, or through any other means.

In **306**, method **300** determines if method **300** iterated through all the nodes since the last nodes iterator reset. This is a conditional statement. If all nodes have been examined, method **300** proceeds to **326**. If nodes remain un-traversed, method **300** proceeds to **308**.

In **308**, method **300** gets the next node using the node iterator. In an embodiment, the first determined node can be the first operation **202**A in data processing pipeline **200**. On subsequent iterations of the looping mechanisms in method **300**, **308** receives a different node. In other words, if method **300** examines operations **202** in FIG. **2**, the initial node obtained could be operation **202**A, followed by operation **202**B, then operation **202**C, etc. In an alternate embodiment, the nodes are not returned numerically or sequentially, but **308** determines the next node randomly, using pointers, or through another suitable methodology by which all nodes in data processing pipeline **200** are ultimately examined. This disclosure will henceforth refer to the node received by **308** as the current node.

In **310**, method **300** resets the neighbor iterator and max gain. The neighbor iterator can be a tool by which to traverse all neighboring clusters of the current node in data processing pipeline **200**. The neighbor iterator traverses all clusters sharing a connection or edge with the current node. The max gain is a variable used to store information as the neighbor iterator traverses each neighboring cluster; summarily, the max gain stores the highest value of moving a node to a neighboring cluster as method **300** iterates through the neighboring clusters.

In **312**, method **300** determines whether all the current node's neighboring clusters were traversed since the last neighbor iterator reset. This is a conditional statement. If all neighboring clusters have been examined, then method **300** proceeds to **322**. If not, then method **300** proceeds to **314**.

In **314**, method **300** obtains the next neighboring cluster of the current node. As indicated in the examples of FIGS. **2**A-**2**B, more than one neighboring cluster may connect to the current node. While the neighboring clusters can be traversed in random, specific, or any other suitable order, the particular order in which the neighboring clusters are traversed is not germane to method **300**. For illustrative purposes, in reference to FIGS. **2**A-**2**B, **314** would determine the neighboring clusters of operation **202**A to be a set containing only cluster **204**B. For further illustration, **314**, if getting the neighboring clusters of operation **202**B, would yield a set of clusters **204**A and **204**C. This disclosure will henceforth refer to the neighboring cluster determined in **314** as the current neighboring cluster.

In **316**, method **300** determines a label intersection between the current node and the current neighboring cluster. In an embodiment, the label for the current node is the programming languages associated with the current node, and the label for the current neighboring cluster is the intersection of all nodes encompassed by the neighboring cluster. Thus, in an embodiment, **316** determines the programming languages shared between the current node and the current neighboring cluster. In other words, **316** takes the intersection between these two sets (the labels of the current node and the labels of the current neighboring cluster) to derive a third set. This disclosure will henceforth refer to this third set of programming languages as the label intersection.

In **318**, method **300** checks if the label intersection (determined in **316**) is null. This is a conditional statement. If the label intersection is null, then method **300** returns to **312** to obtain the next neighboring cluster via the neighbor iterator (and eventually to **322** if all the neighboring clusters of the current node have been examined). If the label intersection is not null, i.e., the label intersection is not the empty set, then method **300** proceeds to **320**.

In **320**, method **300** determines the gain of moving the current node to the current neighboring cluster. In an embodiment, the gain of moving reflects potential gains in efficiency if the current node departs its present cluster for the current neighboring cluster. In an embodiment, **320** determines the gain of moving by examining the number of additional internal connections that would be contained within the current neighboring cluster if it expanded to include the current node, and subtracting this number from the number of additional internal connections that would cross the boundaries between the current node's previous cluster and the new one. **320** also updates the max gain (to the calculated gain of moving) if the calculated gain of moving is higher than the current max gain. A connection is an internal connection if the connection does not cross the boundary between different clusters. Following **320**, method **300** returns to **312**.

In **322** (from **312**), method **300** determines if the max gain is positive, i.e., greater than zero. This is a conditional statement. If the max gain is not positive, method **300** returns to **306**, proceeding to the next node. If the max gain is positive, method **300** proceeds to **324**.

In **324**, method **300** moves the current node to the neighboring cluster with the best cluster. The best cluster is the neighboring cluster with the highest gain of moving. **324** also updates the labels of the cluster that formerly contained the current node and the cluster that now contains the current node. The labels update maintains each cluster's label-set as being the intersection of all of its contained nodes' labels. Method **300** then returns to **306**, proceeding to the next node.

In **326**, which executes after method **300** has iterated across all nodes as determined at **306**, method **300** determines if any improvement occurred since the last complete node iteration. In an embodiment, improvements are any changes to the clustering regime. This is a conditional statement. If improvements occurred, then method **300** returns to **304** and a subsequent node iteration begins. If no improvements occurred during the prior node iteration, method **300** proceeds to **328**.

In **328**, method **300** determines if any improvement occurred since the last graph reduction (a concept discussed in detail below). This is a conditional statement. If no improvement occurred since the last graph reduction, then method **300** proceeds to **332** and method **300** completes. If an improvement occurred since the last graph reduction, then method **300** proceeds to **330**.

In **330**, method **300** performs a graph reduction. A graph reduction is the creation of a new graph where the clusters become nodes of the new graph. The connections between the clusters serve as the connections between the new nodes. Method **300** proceeds to **302**, and a subsequent iteration occurs with the reduced graph reflecting the clustering determination from the previous iteration and the subsequent node iteration acting upon the reduced graph.

FIGS. **4A**-**4D** are flowcharts illustrating an exemplary cluster determination **400**, according to some embodiments. FIGS. **4A**-**4D** provide an example illustration, for exemplary purposes, of method **300** running against an illustrative and theoretical data processing pipeline.

As discussed above, method **300** can be run recursively or iteratively, where subsequent iterations of method **300** traverse the clustering scheme determined by prior iterations. In such an embodiment, the determined clusters would serve as the nodes (operations) in subsequent iterations; the connections between these clusters would be the edges (connections). FIGS. **4A**-**4C** represent a first iteration of method **400**. FIG. **4D** represents the second iteration of method **300**, run against the clusters determined by the first iteration of method **300** in FIGS. **4A**-**4C**.

In FIG. **4A**, **402** portrays the initialization state of an example data processing pipeline. At commencement, the initialized clustering regime has one cluster corresponding to each node in the data processing pipeline. Every node is contained in a cluster, one-to-one. The set of labels for each cluster is to the set of labels for the singular node contained within that cluster.

402 shows the current node at N_0. The max gain is set to 0, and the best cluster is set to null. N_0 has 2 neighboring clusters: C_1 and C_2; these neighboring clusters could be examined in any order. The intersection of the labels of N_0 ($\{1, 2, 4, 5\}$) and C_1 ($\{1, 4, 5\}$) is $\{1, 4, 5\}$, and the gain of moving N_0 to C_1 is 1 because the newly formed cluster would contain 1 connection while losing 0. Because the intersection is not null and the gain of moving is greater than the max gain, the best cluster is set to C_1 and the max gain set to 1. The intersection of the labels of N_0 ($\{1, 2, 4, 5\}$) and C_2 ($\{0, 1, 4, 5\}$) is $\{1, 4, 5\}$, and the gain of moving would also be 1. Because the gain of moving is not greater than the max gain, no further change would be made. Accordingly, method **300** would proceed to a state reflected in **404** with C_1 now containing N_0 and N_1 with a cluster-associated set of labels for C_1 of $\{1, 4, 5\}$.

404 shows the current node at N_1. The max gain is set to 0, and the best cluster is set to null. N_1 has 2 neighboring clusters, C_2 and C_5; these neighboring clusters could be examined in any order. The intersection of the labels of N_1 ($\{1, 4, 5\}$) and C_2 ($\{0, 1, 4, 5\}$) is $\{1, 4, 5\}$, and the gain of moving N_1 to C_2 is 0 because the newly formed cluster would add 1 connection while losing 1 connection. Accordingly, because the gain of moving is not greater than the max gain, no change is made. Regarding C_5, the intersection of the labels of N_1 ($\{1, 4, 5\}$) and C_5 ($\{0, 1, 2, 3\}$) is $\{1\}$, but the gain of moving would also be 0. Because the gain of moving is not greater than the max gain, no change would be made. Accordingly, method **300** would proceed to a state reflected in **406** with no changes made to the clustering regime in **404**.

406 shows the current node at N_2. The max gain is set to 0, and the best cluster is set to null. N_2 has 3 neighboring clusters, C_1, C_4, and C_7; these neighboring clusters could be examined in any order. The intersection of the labels of N_2 ($\{0, 1, 4, 5\}$) and C_1 ($\{1, 4, 5\}$) is $\{1, 4, 5\}$, and the gain of moving N_1 to C_2 is 2 because the newly formed cluster would add 2 more connections while losing 0. Accordingly, because the intersection is not null and the gain of moving is greater than the max gain, the best cluster is set to C_1 and the max gain set to 2. Subsequent examinations of C_4 and C_7 yield a gain of moving of only 1. Accordingly, method **300** would proceed to a state reflected in **408** with C_1 now containing N_0, N_1, and N_2 with a cluster-associated set of labels for C_1 as $\{1, 4, 5\}$.

408 shows the current node at N_3. The max gain is set to 0, and the best cluster is set to null. N_3 has 3 neighboring clusters, C_4, C_5, and C_6; these neighboring clusters could be examined in any order. The intersection of the labels of N_3 ($\{1, 2, 3, 4\}$) and C_4 ($\{1, 2, 3, 5\}$) is $\{1, 2, 3\}$, and the gain of moving N_1 to C_2 is 1 because the newly formed cluster would add 1 more connection while losing 0. Accordingly, because the intersection is not null and the gain of moving is greater than the max gain, the best cluster is set to C_4 and the max gain set to 1. Subsequent examinations of C_5 and C_6 would also find a gain of moving of 1. Because these gains of moving are not greater than the max gain, no further change would be made. Accordingly, method **300** would proceed to a state reflected in **410** with C_4 now containing N_3 and N_4 with a cluster-associated set of labels for C_4 as $\{1, 2, 3\}$.

410 shows the current node at N_4. The max gain is set to 0, and the best cluster is set to null. N_4 has 2 neighboring clusters, C_1 and C_5; these neighboring clusters could be examined in any order. The intersection of the labels of N_4 ($\{1, 2, 3, 5\}$) and C_1 ($\{1, 4, 5\}$) is $\{1, 5\}$, but the gain of moving N_4 to C_1 is 0 because the newly formed cluster would add 1 connection while losing 1 connection. Accordingly, because the gain of moving is not greater than the max gain, no change is made. Regarding C_5, the intersection of the labels of N_4 and C_5 is not null, but the gain of moving would also be 0, so no further change would be made. Accordingly, method **300** would proceed to a state reflected in **412** with no changes made to the clustering regime.

412 shows the current node at N_5. The max gain is set to 0, and the best cluster is set to null. N_5 has 2 neighboring clusters, C_1, and C_4; these neighboring clusters could be examined in any order. The intersection of the labels of N_5 ($\{0, 1, 2, 3\}$) and C_1 ($\{1, 4, 5\}$) is $\{1\}$, and the gain of moving N_4 to C_1 is 1 because the newly formed cluster would add 1 connection while losing 0 connections. Accordingly, because the gain of moving is greater than the max gain, the best cluster is set to C1 and the max gain is set to 1. C_4 is examined next. Here, the intersection of the labels of N_5 ({0, 1, 2, 3}) and C_4 ({1, 2, 3}) is {1, 2, 3}, and the gain of moving would be 2 because the newly formed cluster would add 2 connections while losing 0 connections. Accordingly, because the gain of moving is greater than the max gain, the best cluster is set to C_4 and the max gain is set to 2. Accordingly, method **300** would proceed to a state reflected in **414** with C_4 now containing N_3, N_4, and N_5 with a cluster-associated set of labels for C_4 of {1, 2, 3}.

414 shows the current node at N_6. The max gain is set to 0, and the best cluster is set to null. N_6 has 2 neighboring clusters, C_4, and C_7; these neighboring clusters could be examined in any order. The intersection of the labels of N_6 ({2, 3, 4, 5}) and C_7 ({1, 2, 3, 4}) is {2, 3, 4}, and the gain of moving would be 1 because the newly formed cluster would add 1 connections while losing 0 connections. Accordingly, because the gain of moving is greater than the max gain, the best cluster is set to C_1 and the max gain is set to 1. The intersection of the labels of N_6 ({2, 3, 4, 5}) and C_4 ({1, 2, 3}) is {2, 3}, and the gain of moving N_6 to C_4 is 1 because the newly formed cluster would add 1 connection while losing 0 connections. Accordingly, because the gain of moving is not greater than the max gain, no change is made. Method **300** would proceed to a state reflected in **416** with C_7 now containing N_6 and N_7 with a cluster-associated set of labels for C_7 of {2, 3, 4}.

416 shows the current node at N_7. The max gain is set to 0, and the best cluster is set to null. N_7 has 1 neighboring cluster, C_1. The intersection of the labels of N_7 ({1, 2, 3, 4}) and C_1 ({1, 4, 5}) is {1, 4}, and the gain of moving N_7 to C_1 is 0 because the newly formed cluster would add 1 connection while losing 1 connection. Accordingly, because the gain of moving is not greater than the max gain, method **300** would proceed to a state reflected in **418** with no changes made to the clustering regime.

418 reflects a version of the clustering regime upon completion of the first node. Here, as described in step **326** in relation to method **300**, the node iteration process would repeat because a change had been made. Accordingly, the above iterative steps across all of the nodes would repeat. This second iteration, however, would find no changes to make. For example, though the intersection of the labels of N_1 ({1, 2, 3, 4}) and C_4 ({1, 2, 3}) is not null, the gain of moving N_1 to C_4 is 0 because the newly formed cluster would add 1 connection while losing 1 connection. No gain of moving would be greater than 0 for any of the nodes in the second node iteration. Though in an alternate example subsequent iterations could find additional changes to make and the iterations could continue to occur.

Accordingly, method **300** would proceed to conduct a graph reduction, creating a new graph with the clusters as the nodes of the new graph and the connections between the clusters are the connections between the nodes. Such a reduced graph is reflected in **420**, and the node iteration would commence again acting upon the reduced graph.

420 shows the reduced graph with the current node at N_7. The max gain is set to 0, and the best cluster is set to null. N_7 has 2 neighboring clusters, C_1 and C_4; these neighboring clusters could be examined in any order. The intersection of the labels of N_7 ({2, 3, 4}) and C_4 ({1, 2, 3}) is {2, 3}, and the gain of moving would also be 1. Accordingly, because the gain of moving is greater than the max gain, the best cluster is set to C_4 and the max gain is set to 1. The intersection of the labels of N_7 ({2, 3, 4}) and C_1 ({1, 4, 5}) is {4}, and the gain of moving N_7 to C_1 is 1 because the newly formed cluster would add 1 connection while losing 0 connection. Because the gain of moving is not greater than the max gain, no change is made. Accordingly, method **300** would proceed to a state reflected in **422** with C_4 now containing N_4 and N_7 with a cluster-associated set of labels for C_7 of {2, 3}.

422 shows the current node at N_1. The max gain is set to 0, and the best cluster is set to null. N_1 has 1 neighboring cluster, C_4. The intersection of the labels of N_7 ({2, 3}) and C_1 ({1, 4, 5}) is null. Because the intersection of the labels is null, no change can be made. Accordingly, method **300** would proceed to a state reflected in **424** with no changes made to the clustering regime.

424 shows the current node at N_4. The max gain is set to 0, and the best cluster is set to null. N_4 has 1 neighboring cluster, C_1. The intersection of the labels of N_4 ({1, 2, 3}) and C_1 ({1, 4, 5}) is {1} and the gain of moving would be 1 because 2 connections would be added to the newly formed cluster while losing 1. Accordingly, method **300** would proceed to a state reflected in **426** with C_1 now containing N_1 and N_4 with a cluster-associated set of labels for C_1 of {1}.

426 shows the determined clusters. Data pipeline execution system **106** could subsequently utilize the optimized clustering regime to decide which programming language in which to execute operations **202** in order to avoid computationally expensive throttling between programming languages.

Various embodiments may be implemented, for example, using one or more well-known computer systems, such as computer system **500** shown in FIG. **5**. One or more computer systems **500** may be used, for example, to implement any of the embodiments discussed herein, as well as combinations and sub-combinations thereof.

Computer system **500** may include one or more processors (also called central processing units, or CPUs), such as a processor **504**. Processor **504** may be connected to a communication infrastructure or bus **506**.

Computer system **500** may also include user input/output device(s) **508**, such as monitors, keyboards, pointing devices, etc., which may communicate with communication infrastructure **506** through user input/output interface(s) **502**.

One or more of processors **504** may be a graphics processing unit (GPU). In an embodiment, a GPU may be a processor that is a specialized electronic circuit designed to process mathematically intensive applications. The GPU may have a parallel structure that is efficient for parallel processing of large blocks of data, such as mathematically intensive data common to computer graphics applications, images, videos, etc.

Computer system **500** may also include a main or primary memory **508**, such as random access memory (RAM). Main memory **508** may include one or more levels of cache. Main memory **508** may have stored therein control logic (i.e., computer software) and/or data.

Computer system **500** may also include one or more secondary storage devices or memory **510**. Secondary memory **510** may include, for example, a hard disk drive **512** and/or a removable storage device or drive **514**. Removable storage drive **514** may be a floppy disk drive, a magnetic tape drive, a compact disk drive, an optical storage device, tape backup device, and/or any other storage device/drive.

Removable storage drive **514** may interact with a removable storage unit **518**. Removable storage unit **518** may include a computer usable or readable storage device having stored thereon computer software (control logic) and/or data. Removable storage unit **518** may be a floppy disk, magnetic tape, compact disk, DVD, optical storage disk, and/any other computer data storage device. Removable storage drive **514** may read from and/or write to removable storage unit **518**.

Secondary memory **510** may include other means, devices, components, instrumentalities or other approaches for allowing computer programs and/or other instructions and/or data to be accessed by computer system **500**. Such means, devices, components, instrumentalities or other approaches may include, for example, a removable storage unit **522** and an interface **520**. Examples of the removable storage unit **522** and the interface **520** may include a program cartridge and cartridge interface (such as that found in video game devices), a removable memory chip (such as an EPROM or PROM) and associated socket, a memory stick and USB port, a memory card and associated memory card slot, and/or any other removable storage unit and associated interface.

Computer system **500** may further include a communication or network interface **524**. Communication interface **524** may enable computer system **500** to communicate and interact with any combination of external devices, external networks, external entities, etc. (individually and collectively referenced by reference number **528**). For example, communication interface **524** may allow computer system **500** to communicate with external or remote devices **528** over communications path **526**, which may be wired and/or wireless (or a combination thereof), and which may include any combination of LANs, WANs, the Internet, etc. Control logic and/or data may be transmitted to and from computer system **500** via communication path **526**.

Computer system **500** may also be any of a personal digital assistant (PDA), desktop workstation, laptop or notebook computer, netbook, tablet, smart phone, smart watch or other wearable, appliance, part of the Internet-of-Things, and/or embedded system, to name a few non-limiting examples, or any combination thereof.

Computer system **500** may be a client or server, accessing or hosting any applications and/or data through any delivery paradigm, including but not limited to remote or distributed cloud computing solutions; local or on-premises software ("on-premise" cloud-based solutions); "as a service" models (e.g., content as a service (CaaS), digital content as a service (DCaaS), software as a service (SaaS), managed software as a service (MSaaS), platform as a service (PaaS), desktop as a service (DaaS), framework as a service (FaaS), backend as a service (BaaS), mobile backend as a service (MBaaS), infrastructure as a service (IaaS), etc.); and/or a hybrid model including any combination of the foregoing examples or other services or delivery paradigms.

Any applicable data structures, file formats, and schemas in computer system **500** may be derived from standards including but not limited to JavaScript Object Notation (JSON), Extensible Markup Language (XML), Yet Another Markup Language (YAML), Extensible Hypertext Markup Language (XHTML), Wireless Markup Language (WML), MessagePack, XML User Interface Language (XUL), or any other functionally similar representations alone or in combination. Alternatively, proprietary data structures, formats or schemas may be used, either exclusively or in combination with known or open standards.

In some embodiments, a tangible, non-transitory apparatus or article of manufacture comprising a tangible, non-transitory computer useable or readable medium having control logic (software) stored thereon may also be referred to herein as a computer program product or program storage device. This includes, but is not limited to, computer system **500**, main memory **508**, secondary memory **510**, and removable storage units **518** and **522**, as well as tangible articles of manufacture embodying any combination of the foregoing. Such control logic, when executed by one or more data processing devices (such as computer system **500**), may cause such data processing devices to operate as described herein.

Based on the teachings contained in this disclosure, it will be apparent to persons skilled in the relevant art(s) how to make and use embodiments of this disclosure using data processing devices, computer systems and/or computer architectures other than that shown in FIG. **5**. In particular, embodiments can operate with software, hardware, and/or operating system implementations other than those described herein.

It is to be appreciated that the Detailed Description section, and not any other section, is intended to be used to interpret the claims. Other sections can set forth one or more but not all exemplary embodiments as contemplated by the inventor(s), and thus, are not intended to limit this disclosure or the appended claims in any way.

While this disclosure describes exemplary embodiments for exemplary fields and applications, it should be understood that the disclosure is not limited thereto. Other embodiments and modifications thereto are possible, and are within the scope and spirit of this disclosure. For example, and without limiting the generality of this paragraph, embodiments are not limited to the software, hardware, firmware, and/or entities illustrated in the figures and/or described herein. Further, embodiments (whether or not explicitly described herein) have significant utility to fields and applications beyond the examples described herein.

Embodiments have been described herein with the aid of functional building blocks illustrating the implementation of specified functions and relationships thereof. The boundaries of these functional building blocks have been arbitrarily defined herein for the convenience of the description. Alternate boundaries can be defined as long as the specified functions and relationships (or equivalents thereof) are appropriately performed. Also, alternative embodiments can perform functional blocks, steps, operations, methods, etc. using orderings different than those described herein.

References herein to "one embodiment," "an embodiment," "an example embodiment," or similar phrases, indicate that the embodiment described can include a particular feature, structure, or characteristic, but every embodiment can not necessarily include the particular feature, structure, or characteristic. Moreover, such phrases are not necessarily referring to the same embodiment. Further, when a particular feature, structure, or characteristic is described in connection with an embodiment, it would be within the knowledge of persons skilled in the relevant art(s) to incorporate such feature, structure, or characteristic into other embodiments whether or not explicitly mentioned or described herein. Additionally, some embodiments can be described using the expression "coupled" and "connected" along with their derivatives. These terms are not necessarily intended as synonyms for each other. For example, some embodiments can be described using the terms "connected" and/or "coupled" to indicate that two or more elements are in direct physical or electrical contact with each other. The term "coupled," however, can also mean that two or more elements are not in direct contact with each other, but yet still co-operate or interact with each other.

The breadth and scope of this disclosure should not be limited by any of the above-described exemplary embodiments, but should be defined only in accordance with the following claims and their equivalents.

What is claimed is:

1. A computer implemented method, comprising:

receiving a data processing pipeline comprising operations and connections between the operations,

wherein the operations are programmed in an operation-associated set of programming languages, and

wherein the operations perform a transformational function on a set of data received by the data processing pipeline;

grouping the operations into clusters,

wherein the clusters are each assigned a cluster-associated set of programming languages based on the operation-associated set of programming languages for the operations in the clusters; and

executing the operations in the clusters in a programming language contained in the cluster-associated set of programming languages,

wherein at least one of the receiving, grouping, and executing are performed by one or more computers.

2. The method of claim 1, the grouping the operations into clusters further comprising:

initializing the clusters so that each cluster encompasses one operation, wherein the cluster-associated set of programming languages matches the operation-associated set of programming languages for the encompassed operation;

iterating through the operations, and for each operation:

(1) setting a max gain to zero;

(2) setting a best cluster to null;

(3) determining a set of neighboring clusters for the operation, wherein the set of neighboring clusters are the clusters sharing a connection with the operation;

(4) iterating through the set of neighboring clusters, and for each neighboring cluster:

(a) determining a label intersection;

(b) determining a gain of moving;

(c) setting the max gain to the gain of moving and setting the best cluster to the neighboring cluster if the gain of moving is greater than the max gain and the label intersection is not null; and

(5) moving the operation to the best cluster if the max gain is greater than zero; and

repeating the initializing and iterating against an updated data processing pipeline derived from the prior iteration until an iteration occurs without modifying the clusters.

3. The method of claim 2, the determining a label intersection further comprising:

calculating an intersection between the operation-associated set of programming languages associated for the operation and the cluster-associated set of programming languages for the neighboring cluster.

4. The method of claim 2, the determining a gain of moving further comprising:

counting a number of internal connections added to the neighboring cluster if the operation moves to the neighboring cluster;

counting a number of internal connections lost if the operation moves to the neighboring cluster; and

calculating the gain of moving by subtracting the number of internal connections lost from the number of internal connections added.

5. The method of claim 2, the moving the operation to the best cluster further comprising:

updating the cluster-associated set of programming languages for the best cluster by calculating an intersection of the operation-associated set of programming languages for the operation and the cluster-associated set of programming languages for the best cluster; and

updating the cluster-associated set of programming languages for the operation's prior cluster by calculating an intersection of the sets of programming languages for all operations remaining in the operation's prior cluster.

6. The method of claim 2, wherein the updated data processing pipeline comprises operations set to the clusters determined during the previous iteration, connections between the operations set to the connections between the clusters determined during the previous iteration, and the operation-associated set of programming languages set to the cluster-associated set of programming languages determined during the previous iteration.

7. A system, comprising:

a memory; and

at least one processor coupled to the memory and configured to:

receive a data processing pipeline comprising operations and connections between the operations, wherein the operations are programmed in an operation-associated set of programming languages, and wherein the operations perform a transformational function on a set of data received by the data processing pipeline;

group the operations into clusters, wherein the clusters are each assigned a cluster-associated set of programming languages based on the operation-associated set of programming languages for the operations in the clusters; and

execute the operations in the clusters in a programming language contained in the cluster-associated set of programming languages.

8. The system of claim 7, wherein to group the operations into clusters, the at least one processor is configured to:

initialize the clusters so that each cluster encompasses exactly one operation, wherein the cluster-associated set of programming languages matches the operation-associated set of programming languages for the encompassed operation;

iterate through the operations, and for each operation:

(1) set a max gain to zero;

(2) set a best cluster to null;

(3) determine a set of neighboring clusters for the operation, wherein the set of neighboring clusters are the clusters sharing a connection with the operation;

(4) iterate through the set of neighboring clusters, and for each neighboring cluster:

(a) determine a label intersection;

(b) determine a gain of moving;

(c) set the max gain to the gain of moving and set the best cluster to the neighboring cluster if the gain of moving is greater than the max gain and the label intersection is not null; and

(5) move the operation to the best cluster if the max gain is greater than zero; and

repeat the initialize and iterate steps against an updated data processing pipeline derived from the prior iteration until an iteration occurs without modifying the clusters.

9. The system of claim 8, wherein to determine a label intersection, the at least one processor is configured to:

calculate an intersection between the operation-associated set of programming languages associated for the operation and the cluster-associated set of programming languages for the neighboring cluster.

10. The system of claim **8**, wherein to determine a gain of moving, the at least one processor is configured to:

count a number of internal connections added to the neighboring cluster if the operation moves to the neighboring cluster;

count a number of internal connections lost if the operation moves to the neighboring cluster; and

calculate the gain of moving by subtracting the number of internal connections lost from the number of internal connections added.

11. The system of claim **8**, wherein to move the operation, the at least one processor is configured to:

update the cluster-associated set of programming languages for the best cluster by calculating an intersection of the operation-associated set of programming languages for the operation and the cluster-associated set of programming languages for the best cluster; and

update the cluster-associated set of programming languages for the operation's prior cluster by calculating an intersection of the sets of programming languages for all operations remaining in the operation's prior cluster.

12. The system of claim **8**, wherein the updated data processing pipeline comprises operations set to the clusters determined during the previous iteration, connections between the operations set to the connections between the clusters determined during the previous iteration, and the operation-associated set of programming languages set to the cluster-associated set of programming languages determined during the previous iteration.

13. A non-transitory computer-readable device having instructions stored thereon that, when executed by at least one computing device, causes the at least one computing device to perform operations comprising:

receiving a data processing pipeline comprising operations and connections between the operations, wherein the operations are programmed in an operation-associated set of programming languages, and wherein the operations perform a transformational function on a set of data received by the data processing pipeline;

grouping the operations into clusters, wherein the clusters are each assigned a cluster-associated set of programming languages based on the operation-associated set of programming languages for the operations in the clusters; and

executing the operations in the clusters in a programming language contained in the cluster-associated set of programming languages.

14. The non-transitory computer-readable device of claim **13**, the grouping further comprising:

initializing the clusters so that each cluster encompasses exactly one operation, wherein the cluster-associated set of programming languages matches the operation-associated set of programming languages for the encompassed operation;

iterating through the operations, and for each operation:

(1) setting a max gain to zero;

(2) setting a best cluster to null;

(3) determining a set of neighboring clusters for the operation, wherein the set of neighboring clusters are the clusters sharing a connection with the operation;

(4) iterating through the set of neighboring clusters, and for each neighboring cluster:

(a) determining a label intersection;

(b) determining a gain of moving;

(c) setting the max gain to the gain of moving and setting the best cluster to the neighboring cluster if the gain of moving is greater than the max gain and the label intersection is not null; and

(5) moving the operation to the best cluster if the max gain is greater than zero; and

repeating the initializing and iterating against an updated data processing pipeline derived from the prior iteration until an iteration occurs without modifying the clusters.

15. The non-transitory computer-readable device of claim **14**, the determining a label intersection further comprising:

calculating an intersection between the operation-associated set of programming languages associated for the operation and the cluster-associated set of programming languages for the neighboring cluster.

16. The non-transitory computer-readable device of claim **14**, the determining a gain of moving further comprising:

counting a number of internal connections added to the neighboring cluster if the operation moves to the neighboring cluster;

counting a number of internal connections lost if the operation moves to the neighboring cluster; and

calculating the gain of moving by subtracting the number of internal connections lost from the number of internal connections added.

17. The non-transitory computer-readable device of claim **14**, the moving the operation to the best cluster further comprising:

updating the cluster-associated set of programming languages for the best cluster by calculating an intersection of the operation-associated set of programming languages for the operation and the cluster-associated set of programming languages for the best cluster; and

updating the cluster-associated set of programming languages for the operation's prior cluster by calculating an intersection of the sets of programming languages for all operations remaining in the operation's prior cluster.

18. The non-transitory computer-readable device of claim **14**, wherein the updated data processing pipeline comprises operations set to the clusters determined during the previous iteration, connections between the operations set to the connections between the clusters determined during the previous iteration, and the operation-associated set of programming languages set to the cluster-associated set of programming languages determined during the previous iteration.

19. The method of claim **1**, further comprising:

providing a data configuration tool that displays a visualization of the data processing pipeline comprising the operations used in the processing pipeline, the connections between the operations, and the operation-associated programming languages associated with the operations.

20. The system of claim **7**, wherein the at least one processor is configured to:

provide a data configuration tool that displays a visualization of the data processing pipeline comprising the operations used in the processing pipeline, the connections between the operations, and the operation-associated programming languages associated with the operations.

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